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On the Impact of Market Mergers over Herding: Evidence from EURONEXT

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Abstract

Purpose: To present and empirically test for the first time the hypothesis that herding in a market increases following the market's merger in an exchange group.

Design/methodology/approach: The hypothesis is tested empirically in EURONEXT's four European equity markets (Belgium, France, the Netherlands and Portugal) on the premise of the Hwang and Salmon (2004) measure which allows us insight into the significance, structure and evolution of market herding. Tests are conducted for each market for the period prior to and after its merger into EURONEXT, controlling for a series of variables (market conditions, common risk factors, size) to gauge the robustness of our findings.

Findings: Results indicate that, with the exception of Portugal, herding grows in significance, yet declines in momentum post-merger. We ascribe our findings to EURONEXT's enhanced transparency (which makes it easier for investors to observe their peers' trades, thus allowing them to infer and free-ride on their information) and its fast-moving informational dynamics that render herding movements shorter-lived. These results are robust when controlling for various market states and common risk factors, with deviations being observed when controlling for size and market volatility.

Originality/value: Our study presents results for the first time on the impact of exchange mergers on herd behavior. We believe these to constitute useful stimulus for further research on the issue and bear important implications for regulators/policymakers in view of the ongoing proliferation of exchange mergers that has been underway since the 1990s.

Keywords: Herding; Behavioral Finance; Exchange Mergers; EURONEXT

Article classification: Research Paper

1. Introduction

A key development of the last two decades that has gradually been transforming the institutional landscape of capital markets is that of mergers among stock exchanges. Motivated by the needs of national markets to enhance their viability and competitiveness in an increasingly globalized financial system, these mergers have given rise to cross-border exchange groups of regional or global dimensions (McAndrews and Stefanadis, 2002). Despite the fact that exchange mergers transform a market's dynamics by allowing it to become part of a group of markets bearing a common trading system and harmonized institutional frameworks (Nielsson, 2009), to date no study has explored their impact on investors' behavior in the participating stock exchanges. In recent years much attention has been given to the issue of herding in financial markets (as evidenced by a series of studies confirming its presence internationally [1]), in light of the view that herding directly impacts asset prices and has important implications for investors. In the context of their relative performance assessment and the principal-agent considerations involved, fund managers, for example, often tend to copy each other in order not to deviate from their industry's average (see e.g. Wermers, 1999); given the importance of funds in modern capital markets, such behavior would be expected to have a significant impact upon securities' prices. Since market mergers are likely to impact both on a market's investor-composition and its transparency, it is surprising that the impact of market mergers on this aspect of behavior has not been investigated. It is this issue which we seek to address in this paper.

Specifically, drawing on the extant literature, we explain why market mergers may promote herding and empirically test for this in the context of EURONEXT's four European [2] equity markets (Belgium, France, the Netherlands and Portugal). Our results indicate that herding grows in significance following EURONEXT-membership; more specifically, while herding was found to be significant pre-merger only in the Netherlands, it appears significant post-merger in Belgium, France and the Netherlands (herding significance is not detected in Portugal, the smallest market by value in our sample, in either period). We attribute this increase in herding post-merger in the group's three largest European markets to the rise in volume due to higher overseas investors' participation post-merger (which helped increase the flow of information [3]) and EURONEXT's enhanced transparency (which allowed uninformed investors to infer and free-ride on this information by making it easier for them to observe the trades of their informed peers). In terms of its structure, herding in the three main markets is characterized by reduced persistence and more noise post-merger, consistent with improved informational dynamics motivated by EURONEXT's sophisticated environment. Such a change in the environment helps to reduce the momentum of directional herding movements. These findings are robust to tests controlling for different market states and common risk factors. However, the pattern is sensitive to market volatility and size.

We believe our work provides important insights into the literature on the effect of the institutional environment on herding (e.g. Voronkova and Bohl, 2005; Goodfellow et al, 2009). It is also of interest to regulatory authorities and policymakers given the proliferation of stock exchange alliances worldwide, reflecting the increased integration of capital markets and the fact that the prevalence of herding can lead prices to exhibit large departures from their fundamental values and give rise to destabilizing outcomes (Goodhart et al., 1999) [4].

The rest of the paper is organized as follows: the next section discusses why exchange mergers may boost herding in the participating markets based on both behavioral as well as non-behavioral arguments. Section 3 presents an overview of the EURONEXT, while section 4 introduces the data and methodology used in this research and presents some descriptive statistics. Section 5 outlines and discusses the results and section 6 concludes.

2. Herd Behavior and Market Mergers

Herding refers to the type of conduct involving similarity in behavior following interactive observation of beliefs, actions or action-payoffs (Hirshleifer and Teoh, 2003). When investors find themselves in a state of imitation they tend to exhibit intentional disregard both for fundamentals as well as their own private information, seeking instead refuge in the consensus (Bikhchandani and Sharma, 2001). In *behavioral* terms, several psychological forces have been found to underlie the decision to herd, including the conformity bias (Hirshleifer, 2001), the congruity bias (Prast, 2000), and the home bias (Feng and Seasholes, 2004). From a *rational* viewpoint, investors may choose to herd in anticipation of informational payoffs, free-riding on the information of those they perceive as better informed by copying their actions (Devenow and Welch, 1996), thus leading to temporary blockages in the aggregation of information into prices and fostering informational cascades (Banerjee, 1992; Bikhchandani et al, 1992). Agency concerns arising from the relative (versus their peers) periodic assessment of their performance can promote herding among finance professionals (e.g. fund managers), as they can lead those of "weak" ability/reputation to copy the behavior of their "strong" peers (Scharfstein and Stein, 1990; Trueman, 1994). In this paper we test the hypothesis that the merger of a stock market into an exchange group leads to an increase in herding. The hypothesis is motivated by both behavioral and rational arguments, each of which will be discussed in turn.

i. Behavioral dimension

The behavioral impact of a market's merger on herding hinges upon the well-documented issue of the home-bias, namely the preference of individuals towards stocks of companies located closer to "home". The concept of "home" can assume various connotations, including that of an individual's neighbourhood, hometown, region or country (Bailey et al, 2008).

Evidence in favor of the home-bias has been reported both for retail investors (Grinblatt and Keloharju, 2001; Feng and Seasholes, 2004; Ivkovich and Weisbenner, 2005; Seasholes and Zhu, 2010) as well as for fund managers (Coval and Moskowitz, 1999, 2001; Hong et al, 2005; Baik et al, 2010), with results showing a higher correlation among investors' trades for stocks whose underlying companies are geographically proximate to these investors' homes. The fact that home-bias leads investors to exhibit similarity in their trades (i.e. herding) has been ascribed by Kuran and Sunstein (1999) to availability cascading. By encouraging social preference towards "home" stocks in a community, home-bias leads the community's pool of information to be dominated by information regarding those stocks only, thus enhancing the availability bias in stock-selection towards "home" stocks. Furthermore, Huberman (2001) provides evidence suggesting that home-bias is the outcome of familiarity-bias; investors prefer stocks which appear more familiar to them. If such a mentality is widespread in a community, then conformity bias (Hirshleifer, 2001) can also contribute to home-bias, since the tendency to conform to the norm (in this case, the preference for local stocks) would enhance similarity in trading among its members.

The merger of a market into an exchange group initiates a process of financial integration for that market which is expected to affect its local investors' home-bias (Ferrando and Vesala, 2005). In operational terms, exchange groups essentially function as single exchanges with all member-markets being subject to a uniform regulatory framework setting out the rules for the implementation of a harmonized trading protocol. The stocks of all constituent markets are traded subject to this protocol whose application involves the adoption of a common trading system ("platform") by all member-markets, allowing the stocks of each to be traded through that platform from any of the group's other markets [5]. An environment like this bears an impact on the availability and familiarity biases that underlie investors' home-bias as it promotes ease of trading (investors in any member-market can view trading in another member-market as being as easy as trading in their home market) and wider information diffusion (it allows information on each member-market to be more readily available to investors of the other member-markets). Consequently, we would expect investors from one market in the group to perceive the other markets' stocks as less "distant" (Giofré, 2008), thus leading them to gradually expand the concept of "home" in their perception and identify it with the whole group. This implies that traders from each member-market will, over time, begin to monitor the other markets and observe signals similar to those of local investors in each. As a result, the number of investors with correlated signals in each market will increase, thus increasing the likelihood of herding in their actions (Graham, 1999) [6].

ii. Rational dimension

Market mergers also impact on herding due to the effect of the group's institutional environment on the learning process of its investors. Exchange groups promote financial integration by unifying the trading and clearing activities across their participating markets through their single platform (Nielsson, 2009). Combined with the anticipated reduction in trading costs (Domowitz and Steil, 2002; Schmiedel et al, 2006), this encourages intra-group trading, thus widening the pool of potential investors for each member-market and enhancing the flow of trades (and, thus, information) across member-markets. Such conditions have been found to contribute positively to liquidity (Arnold et al, 1999; Pagano and Padilla, 2005; Nielsson, 2009), thus leading information to be reflected into prices at an accelerated rate. Although this should lead investors to rely less on the consensus and remove much of the ground for herding, the very transparency promoted through such conditions facilitates the observation of others' actions as a legitimate mode of social learning if these actions are actually believed to reflect valuable information (Teraji, 2003).

Vives (1993) and Cao and Hirshleifer (1997) raise the possibility of investors basing their learning process upon prices, as the latter constitute a noisy statistical summary of other investors' actions. Observing the price-generation process constitutes a useful input to investors' learning because it allows them to tacitly infer the trading of other investors at the aggregate level without having to make a potentially costly effort to actually observe them individually. Hence, prices in this case function as a consensus-indicator whose precision (and credibility) will grow if pricing-efficiency improves as a result of the platform. Since the probability of people herding towards the consensus-opinion increases with the accuracy of the latter (Teraji, 2003), it follows that we would expect an increase in herding following market mergers if investors undertake indirect observational learning.

Secondly, there exists the expectation that membership in an exchange group will reduce transaction costs. Microstructure research (Lee, 1998; Romano, 2007) indicates that transaction costs prevent traders from revealing their information in a timely manner, thus creating a "backlog" of hidden information, whose failure to be aggregated into prices leads to cascades [7]. Herding under these conditions grows in persistence (the number of investors delaying trading on their information rises with the duration of the cascade, thus prolonging it), yet cannot be considered significant (it is sustained by limited participation). A decline in transaction costs is expected to increase the participation of informed investors as trading in a market with less frictions is more appealing, thus allowing information to be more easily revealed through their trades. This will make it easier for uninformed investors to observe the trades of their informed counterparts and mimic them in pursuit of informational payoffs, thus leading to an increase in herding following a market's merger into a group.

A third issue involves observational learning, specifically of institutional investors, by far the dominant investor-group in today's markets (Choi and Sias, 2009). More specifically, the reduced risk-perception associated with a highly transparent environment encourages fund managers in possession of good-quality information to trade on it, while at the same time provides for improved disclosure and reporting requirements (Gelos and Wei, 2005). "Weak" fund managers motivated by the anticipation of career/reputational payoffs could exploit this transparency to identify the actions of their "strong" peers more easily and mimic them in order to free-ride on their informational content (Holmes et al, 2011) [8], thus giving rise to increased herding in a market following its merger into a group.

As the above discussion indicates, there exist arguments both from the behavioral as well as the rational side suggesting an increase in a market's herding following its merger into a group. The issue has serious regulatory and policymaking implications, more so in view of the proliferation of exchange consolidations undertaken since the 1990s internationally. A rise in herding can have undesirable consequences as it can lead to destabilizing outcomes, thus increasing a market's risk. Therefore, we believe our study contributes significantly by examining this issue empirically in the context of EURONEXT, one of the first exchange groups to have been established internationally.

3. EURONEXT: An Overview

Exchange groups are the products of an evolutionary process dating back to the 1990s, a decade characterized by the liberalization of international portfolio flows, a surge in technological innovations and the gradual demutualization of stock exchanges (Aggarwal and Dahiya, 2006). This encouraged cross-listings, as companies began seeking access to capital overseas, thus stirring up the competition for liquidity among stock markets to prevent companies and investors from migrating to markets offering better terms of trading (Nielsson, 2009). To that end, markets began to invest heavily in new financial products and their technological infrastructure (to enable them to handle ever-increasing volumes of trade), yet the growing costs involved led them to join forces and form cross-border groups in order to benefit from synergies. In this context, EURONEXT came into existence as an entity in September 2000 as the product of the merger between the Belgian, French and Dutch capital markets, which unified their equity, derivatives and clearing segments. The group expanded through the acquisition of the LIFFE [9] (January 2002) and the Lisbon stock exchange (Portuguese stocks were first included in the group's main indices [10] in April 2002), before entering a merger agreement with the New York stock exchange in 2007.

Equity trading on the group's common platform is modeled after the Nouvelle Système de Cotation (NSC) of the Paris market (formerly known as the [or La] Cotation Assisté en Continue – CAC - first introduced in 1986) which was based on an electronic public limit-order book (Pagano and Padilla, 2005). Highly liquid stocks are traded in a dual (call-auction and continuous) trading system, whereas less liquid ones are subject to double-auction trading with ad hoc market makers ensuring the provision of liquidity (Kasch-Harotounian and Theissen, 2009). The platform is characterized by enhanced transparency, both pre- and post-trade, since traders can observe the entire order book and the trades recorded by the system, while the five best bid/ask offers in terms of price and quantity are publicly disseminated (Ginglinger and Hamon, 2007). Limits to this transparency are set by the presence of "iceberg" orders (i.e. orders whose volume is partitioned in equal-sized tranches, with the visibility of each being conditional upon the execution of the previous one), as well as the anonymity [11] of orders and trades (De Winne and D'Hondt, 2005).

Table 1 presents data on the trading volume and market capitalization of the Belgian, French, Dutch and Portuguese equity markets for the 2003-2008 period [12], which is reflective of an increasing trend [13] in liquidity for all four markets. As the table shows, France is by far the largest market in terms of both capitalization and volume, followed by the Netherlands, Belgium and Portugal. Table 2 presents data on the shareholder-ownership in each of these four markets, revealing an increase in the position of foreign investors in the market capitalization of Belgium, France and the Netherlands following 2000 [14]. Although it is impossible to assess the extent to which intra-group trading contributed to this increase, the figures nevertheless suggest that overseas traders had a role in the enhancement of the post-merger liquidity of these markets.

[Insert Tables 1, 2 about here]

4. Data and Methodology

Our study involves daily data on the closing prices and market capitalizations of the universe of ordinary stocks listed on EURONEXT's four European equity markets (Belgium, France, the Netherlands and Portugal) for the period 1/1/1993 – 31/10/2009. The fifth equity market in EURONEXT – the NYSE – is not included in the analysis given the very short post-merger window (less than two years) for NYSE, notwithstanding the fact that given the NYSE's size, the merger is expected to have less impact on this market. The choice of January 1993 as the start-date for our sample window is due to the limited availability of data for Portuguese stocks prior to 1993. To mitigate the possibility of a survivorship bias, our sample includes both active stocks as well as those that have been delisted at some point throughout the sample period in each market. Our final sample includes 4,164 stocks: 286 listed in Belgium; 2,941 in France; 716 in the Netherlands; and 221 in Portugal. All data used were obtained from the Thomson-Reuters Datastream database.

The empirical design is based upon the herding measure proposed by Hwang and Salmon (2004) for two reasons. First of all, unlike previous herding measures (Christie and Huang, 1995; Chang et al., 2000) that test for the presence of herding conditional upon various market states (e.g. "extreme" returns or up/down markets), Hwang and Salmon (2004) measure herding without restricting its investigation to any specific market states. Secondly, their model is the first framework capable of providing insight into the structure of herding, while also allowing its evolution over time to be visualized graphically.

The rationale underlying Hwang and Salmon (2004) is essentially that, when investors are driven by behavioral biases, their perceptions of the risk-return relationship of assets may be distorted. If they do herd towards the market consensus, then it is possible that as individual asset returns follow the direction of the market return, their betas will deviate from their equilibrium values. Thus, the beta of a stock does not remain constant, but changes with fluctuations in investors' sentiment. As a result, the cross-sectional dispersion of the stock-betas would also be expected to be smaller, i.e. asset betas would tend towards the value of the market beta, namely unity. More specifically, they assume the equilibrium beta (β_{imt}) and its behaviorally biased version (β^b_{imt}), are related as follows:

$$\left(E^b_t(r_{it}) \;/\; E_t(r_{mt}) \right) = \beta^b_{imt} = \beta_{imt} - h_{mt}\,(\beta_{imt} - 1) \tag{1}$$

where $E^b_t(r_{it})$ is the behaviorally biased conditional expectation of excess returns of asset *i* at time *t*, $E_t(r_{mt})$ is the conditional expectation of excess returns of the market at time *t* and $h_{mt} \leq 1$ is a time-variant herding parameter. To measure h_{mt} (herding) on a market-wide basis, the authors calculate the cross-sectional dispersion of β^b_{imt}, as:

$$Std_c(\beta^b_{imt}) = Std_c(\beta_{imt})\,(1 - h_{mt}) \tag{2}$$

Equation (2) is rewritten as follows:

$$\log\left[Std_c(\beta^b_{imt}) \right] = \log\left[Std_c(\beta_{imt}) \right] + \log(1 - h_{mt}) \tag{3}$$

in order to extract h_{mt}.

Finally, (3) is written as follows:

$$\log\left[Std_c(\beta^b_{imt}) \right] = \mu_m + H_{mt} + \upsilon_{mt} \tag{4}$$

where

$$\log [\, Std_c(\beta_{imt}) \,] = \mu_m + \upsilon_{mt} \tag{5}$$

with $\mu_m = E\,[\log [\, Std_c(\beta_{imt}) \,]]$ and $\upsilon_{mt} \sim$ iid $(0,\ \sigma^2_{m,\upsilon})$

and $H_{mt} = \log(1 - h_{mt})$ (6)

Hwang and Salmon (2004) assume that the herding parameter follows an AR(1) process and their model becomes:

$$\log [\, Std_c(\beta^b_{imt}) \,] = \mu_m + H_{mt} + \upsilon_{mt} \tag{7}$$

$$H_{mt} = \phi_m H_{m,t-1} + \eta_{mt} \tag{8}$$

Equations (7) and (8) are estimated for each of EURONEXT's four European equity markets (Belgium, France, the Netherlands and Portugal) and where $\eta_{mt} \sim$ iid $(0,\ \sigma^2_{m,\eta})$.

The above system of equations (7) and (8) accommodates herding as an unobserved component; to extract the latter, Hwang and Salmon (2004) employ the Kalman filter. Thus, in the above setting, the log [$Std_c(\beta^b_{imt})$] is expected to vary with herding levels, the change in which is reflected through H_{mt}. The log [$Std_c(\beta^b_{imt})$] here is equal-weighted, since each beta is assumed to bear equal weight in its calculation.

To construct the log [$Std_c(\beta^b_{imt})$], we employ OLS-estimates of the betas of market returns obtained through Carhart's (1997) four-factor model:

$$r_{itd} = \alpha^b_{it} + \beta^b_{imt}\, r_{mtd} + \beta^b_{iSt}\, SMB_{td} + \beta^b_{iHt}\, HML_{td} + \beta^b_{iWt}\, WML_{td} + \varepsilon_{itd} \tag{9}$$

using daily excess [15] returns within monthly windows for each market. SMB and HML in equation (9) are the established Fama and French (1993) factors capturing the impact of Size and Book-to-Market, respectively, while WML is Carhart's (1997) momentum factor [16]; finally, the subscript *td* indicates daily data *d* for month *t*. The choice of Carhart's (1997) model here constitutes an improvement compared to Hwang and Salmon (2004) who based their beta-estimations on the CAPM and the Fama-French (1993) three-factor models given that the momentum it takes into account as a risk-factor is one of the most robust anomalies in the finance literature (Griffin *et al.*, 2003; Nijman et al., 2004; Fama and French, 2008). Having estimated these monthly betas for each market's stocks in month *t*, we estimate their cross-sectional standard deviation for that month for each market, thus constructing a monthly time-series. As Hwang and Salmon (2004) argued, the choice of monthly windows is driven by both estimation considerations (to reduce the estimation error of the betas) as well as practical ones (to maintain a number of observations sufficient to detect herding).

The significance of herding is inferred from the pattern of H_{mt}. If $\sigma^2_{m,\eta}$ = 0, then H_{mt} = 0 and there is no herding. Conversely, a significant value of $\sigma^2_{m,\eta}$ would imply the existence of herding whose first-order autoregressive structure would further be confirmed by a significant value for ϕ_m, the latter reflecting the persistence of herding. The absolute value of ϕ_m is taken to be smaller than or equal to one, since, as Hwang and Salmon (2004) posit, herding would not be expected to be an explosive process. Consequently, the joint significance of $\sigma^2_{m,\eta}$ and ϕ_m is necessary for herding to be considered statistically significant.

However, the herding estimate obtained from the set of equations (7) and (8) is extracted under the assumption that herding is the sole factor underlying the variations of the log[$Std_c(\beta^b_{imt})$]. In reality, such variations may be influenced by several other factors, including, for example, the state of the market, other common risk pricing factors or macroeconomic conditions. Therefore, we examine the robustness of our results to the inclusion of variables reflective of the state of the market, namely market volatility and market direction. Equation (7) would now be extended in each of these cases as follows:

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_m + c_1 r_{m,t} + \upsilon_{mt} \quad (10)$$

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_m + c_2 \log \sigma_{m,t} + \upsilon_{mt} \quad (11)$$

where $r_{m,t}$ is the monthly return of each market's index [17] and $\log\sigma_{m,t}$ is the monthly log-volatility of each index calculated here using the Schwert (1989) approach.

We then move on to explore the impact of established common risk-pricing factors, namely Size, Book-to-Market (Fama and French, 1993) and Momentum (Carhart, 1997) over our estimated herding by augmenting equation (7) in each case as follows:

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_m + c_3 SMB_t + \upsilon_{mt} \tag{12}$$

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_m + c_4 HML_t + \upsilon_{mt} \tag{13}$$

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_m + c_5 WML_t + \upsilon_{mt} \tag{14}$$

To assess the impact of macroeconomic conditions over the significance of the estimated herding, we include the Treasury bill rate [18] (a proxy for the cost of credit) in equation (7):

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_m + c_6 TB_t + \upsilon_{mt} \tag{15}$$

We also run the set of equations (7)-(8) one more time with all the control variables used jointly in the estimation, as follows:

$$log[\,Std_c(\,\beta^b_{imt}\,)] = \mu_m + H_m + c_1 r_{m,t} + c_2 \sigma_{m,t} + c_3 SMB_t + c_4 HML_t + c_5 WML_t + c_6 TB_t + \upsilon_{mt} \tag{16}$$

As the above estimations are undertaken on the premise of equal-weighted cross-sectional beta-dispersions, we control for the possibility of any size-effect in our estimates by calculating the value-weighted version of the cross-sectional standard deviation of the betas:

$$Std^v_c(\beta^b_{imt}) = \sqrt{\sum_{i=1}^{N_t} w_{it}(\beta^b_{imt} - \overline{\beta}^{b,v}_{imt})^2} \tag{17}$$

where $\overline{\beta}^{b,v}_{imt}$ is the capitalization-weighted average of the stock betas, N_t is the total number of active stocks each month in each market and w_{it} the weight in each market of stock i at month t (Hwang and Salmon, 2004).

To test through the above empirical specifications whether the merger of a market into EURONEXT has had an effect over the significance of herding, we define the pre- and post-merger periods in line with our discussion in section 3; more specifically, we assume October

2000 as the break-point of our sample window for our estimations for Belgium, France and the Netherlands and April 2002 for Portugal. The pre-merger period for Belgium, France and the Netherlands is January 1993 – September 2000; for Portugal it is January 1993 – March 2002. On the other hand, the post-merger period for Belgium, France and the Netherlands is October 2000 – October 2009; for Portugal it is April 2002 – October 2009.

Table 3 presents some statistics related to the logarithmic cross-sectional standard deviation of the betas, both equal- (panel A) and value-weighted (panel B), for each of EURONEXT's four European markets before and after their EURONEXT-membership. As indicated by the table, the logarithmic cross-sectional standard deviation of the betas exhibits insignificant skewness and kurtosis, while the Jarque-Bera statistic does not indicate any departures from normality. Therefore, the state-space model of Hwang and Salmon (2004) described previously can be legitimately estimated using the Kalman filter.

[Insert Table 3 about here]

5. Results and Discussion

We test for the impact of each market's merger into EURONEXT upon its herding using nine different specifications of the Hwang and Salmon (2004) model as described in the previous section. Tables 4-7 contain the results from these tests. Our interest is concentrated on the estimates of the parameters of the state-equation (8), namely ϕ_m and $\sigma^2_{m,\eta}$, since significant values for those two jointly would indicate the presence of significant herding. For each test we also report the value of the signal-to-noise ratio which is calculated by dividing $\sigma_{m,\eta}$ by the time series standard deviation of the log[$Std_c(\beta^b_{imt})$] and indicates what proportion of the variability of the log[$Std_c(\beta^b_{imt})$] is explained by herding; as Hwang and Salmon (2004) showed, the bigger its value, the noisier herding evolves over time.

Results indicate an overall increase in herding following the merger into EURONEXT. More specifically, $\sigma^2_{m,\eta}$ is universally insignificant pre-merger for Belgium (table 4; panel A), France (table 5; panel A) and Portugal (table 7; panel A), thus indicating the absence of significant herding in these markets pre-merger. Evidence of herding significance pre-merger is confined to the Netherlands, since as table 6 (panel A) shows, ϕ_m and $\sigma^2_{m,\eta}$ are jointly significant for most specifications of the Hwang and Salmon (2004) model tested. Conversely, ϕ_m and $\sigma^2_{m,\eta}$ are found to be jointly significant for most post-merger tests in Belgium (table 4; panel B), France (table 5; panel B) and the Netherlands (table 6; panel B), thus indicating the presence of significant herding post-merger in the three largest European markets of EURONEXT [19]. The above pattern appears overall consistent across these three markets, with exceptions arising for the test controlling for volatility, the test controlling for all variables jointly and the value-weighted test, which will be discussed in more detail below. Regarding Portugal (the smallest of the four European member-markets) herding remains insignificant post-merger (table 7; panel B).

The overall post-merger increase in herding confirms our predictions regarding the anticipated effect of a market's merger on herding. However, additional insight can be provided by looking at changes in the herding structure which suggest that herding generally becomes less persistent (ϕ_m declines) and noisier (the signal-to-noise ratio rises) post-merger in EURONEXT's three biggest European markets. To illustrate this, consider the example of France (table 5). As panel A of that table indicates, ϕ_m assumes values over 0.8 (with the exception of the value-weighted test where it equals 0.75) pre-merger, with its post-merger values (panel B) hovering between 0.56 and 0.61 (with the exception of the test controlling for all variables jointly and the value-weighted test [20]). In terms of its signal-to-noise ratio, in 6 of the 9 specifications the value post-merger is markedly higher than the value pre-merger; it never exceeds 0.23 pre-merger (panel A), yet produces much higher values post-merger, in excess of 0.5 (with the exception of the test controlling for volatility, the test controlling for all variables jointly and the value-weighted test [21]). With ϕ_m being the first-order autocorrelation coefficient of H_{mt}, a decline in this parameter's value would imply a weaker dependence of current values of H_{mt} upon their one-period lagged values. As H_{mt} reflects the relative change in the level of herding, this suggests that the effect of previous changes in herding upon its contemporaneous changes grows weaker.

A possible interpretation of herding appearing to be mostly insignificant pre-merger can be traced in the lower pre-merger volumes in each market not allowing the formation of widely followed cascades. Any cascade developing pre-merger would, thus, have been based on little participation (and information) and would have been expected to last for longer (the smaller pre-merger volumes would have rendered it more difficult for sufficient information to flow into the market and dislodge it), thus resulting in herding appearing smoother directionally (lower pre-merger signal-to-noise ratio values). The rise in herding significance post-merger in Belgium, France and the Netherlands needs to be assessed in view of the wider participation, especially on behalf of overseas investors (see table 2), encouraged by EURONEXT. As the evidence presented in table 1 indicates, this helped boost the volume of trade and, in view of overseas investors' perceived sophistication, allowed for more information to enter each member-market [22]. In view of EURONEXT's enhanced transparency facilitating the observation of their informed peers' trades, uninformed investors would find it easier to tacitly infer (and free-ride on) their information; this, in turn, would encourage herding, something further confirmed by our post-merger results.

However, such conditions also affected the duration of herding, since they rendered the prolonged persistence of any cascade difficult to sustain due to informational reasons. This is because the enhanced information flow achieved through EURONEXT's sophisticated trading system creates an environment whose state is constantly changing, rendering cascading on any piece of information very fragile, since the high arrival rate of signals into the market increases the probability that a new signal capable of dislodging the cascade will arrive (Moscarini et al, 1998). The above, therefore, helps explain why herding post-merger is found to be significant, albeit short-lived in its directional movements and exhibits more noise in its evolution in EURONEXT's three largest European markets.

[Insert Tables 4,5,6,7 about here]

The significance of herding in Belgium, France and the Netherlands post-merger exhibits a decline when controlling for size, volatility and all control variables jointly. Regarding size, herding is insignificant in France post-merger for the value-weighted test, since, as table 5 (panel B) indicates, both ϕ_m and $\sigma^2_{m,\eta}$ are found to be insignificant for that test. As Hwang and Salmon (2004) suggested, a possible explanation for this is that there exists little herding among larger capitalization stocks and more among smaller capitalization stocks [23].
Controlling for volatility and controlling for all variables jointly renders herding insignificant post-merger for Belgium (table 4; panel B) and France (table 5; panel B), since in both markets $\sigma^2_{m,\eta}$ is found to be insignificant for those two tests. Suspecting a possible volatility-effect, we repeated the post-merger tests for these two markets controlling for all variables excluding volatility. Results from these additional tests indicated the presence of significant herding post-merger for Belgium and France, thus confirming the presence of a volatility-effect [24, 25] which we consider to be a very interesting finding. With herding defined in the Hwang and Salmon (2004) context as a reduction in the log[$Std_c(\beta^b_{imt})$] due to H_{mt}, this implies that changes in the log[$Std_c(\beta^b_{imt})$] can also be explained by changes in market

volatility, instead of herding alone, possibly because both volatility and herding are capturing parallel, information-driven dynamics. According to Ross (1989), volatility constitutes a proxy for information-flow, thus suggesting that the higher the participation of informed traders in a market, the higher its volatility is expected to be; however, the participation of informed investors tends to be more pronounced in markets with high transparency (Gelos and Wei, 2005) and transparency can encourage herding tendencies on behalf of uninformed investors in these markets as it facilitates the observation of informed investors' trades.

To visualize the evolution of herding over time we present results graphically. We first extract h_{mt} (according to equation (6), $h_{mt} = 1 - \exp(H_{mt})$) and then plot it (Figures 1-4) for each market [26]. We present here each market's herding graphs for three specifications: the original one; the value-weighted one; and the one controlling for all control variables jointly. Other graphs displayed similar patterns with those from the above three specifications [27]. More specifically, the herding graphs produced controlling for market direction, SMB, HML, WML and the Treasury bill rate exhibited overall similarity to the graphs from the original model in all four markets. The impact of volatility over our herding estimations mentioned previously was also noted in the graphical representations of herding, since the herding graph extracted controlling for volatility was similar to that extracted controlling for all variables.

[Insert Figures 1,2,3,4 about here]

Looking at figures 1-4 we notice that herding has evolved in each market in a distinctive fashion for each of the three specifications for which graphs are presented. It is clear that periods of well-known financial crises are associated with reversals in the course of herding, in line with Hwang and Salmon (2004). One such case is that of the year 1994, a year marked by the outbreak of the currency crisis in Latin America, where herding appears (in most graphs) to rise (and peak) before starting to descend. Another case relates to the second half of the 1990s, a period characterized by several financial episodes, including the Asian crisis (1997-8), the Russian crisis (1998) and the Dot.Com bubble-crash (1998-2000). Finally, herding is found to exhibit a peak (and subsequent reversal) in several of our figures during the last quarter of 2008, a point in time coinciding with the outbreak of the global credit crisis [28]. A possible explanation for herding reversing its ascending course during crisis-periods is that financial crises render the market environment more informative as they help reveal information which for some reason (e.g. pre-crisis irrational exuberance) was not incorporated into the public pool of information earlier (Borio, 2008). The revelation of new fundamentals reflective of the true state of the market removes the salience of the pre-crisis consensus opinion (it now becomes obsolete since it was formed upon pre-crisis beliefs) and this adversely affects the herding nurtured by this consensus.

6. Conclusion

This paper proposes for the first time the hypothesis that herding in a market rises following the market's merger into an exchange group. We first explain why market mergers may promote herding and then empirically test for this in the context of EURONEXT's four European equity markets (Belgium, France, the Netherlands and Portugal). Our results lend support to this hypothesis, as herding pre-merger is found to be significant only in the Netherlands, yet appears significant post-merger in Belgium, France and the Netherlands (with no evidence of herding in the smallest market, Portugal). We attribute this pattern in the three biggest markets to the rise in volume post-merger due to higher overseas traders' participation (with the exception of Portugal, where overseas participation did not exhibit a notable change following its merger into EURONEXT) which led to more information flowing into these markets and EURONEXT's enhanced transparency (which allowed uninformed investors to infer and free-ride on this information by making it easier for them to observe the trades of their informed peers). In terms of structure, herding in the three largest markets grows less persistent and noisier post-merger and we ascribe this to the higher information-flow and changeability of the EURONEXT-environment which reduces the duration of the directional herding movements. The pattern witnessed in EURONEXT's three largest European markets post-merger (herding growing more significant, less persistent and noisier) proves robust for several tests performed to control for different market states and common risk factors. Tests controlling for market volatility (in Belgium and France) and size (in France) were less clear cut. Regarding size, the post-merger herding insignificance observed in our value-weighted test in France implies that herding there was mostly due to smaller stocks; in the case of volatility, we argue that herding grows insignificant (in Belgium and France) when controlling for it due to volatility and herding capturing parallel, information-driven dynamics.

These results have important implications for regulatory authorities and policymakers, given the proliferation of exchange mergers since the 1990s. Although our findings indicate overall that merging into an exchange group tends to boost the significance of a market's herding, the fact that herding post-merger generates shorter directional movements suggests that any impact it may have in the market is short-lived, thus reducing the potential for destabilization. This evidence is encouraging as regards the evolution of exchange groups as it indicates that their sophisticated structures are capable of preventing prolonged herding episodes, thus being conducive to market stability.

Notes

1. Evidence in favor of herding has been documented for both developed (e.g. Choi and Sias, 2009) as well as emerging capital markets (e.g. Holmes et al, 2011).

2. The explicit reference to "European" here is due to the fact that EURONEXT recently (2007) entered into a merger-agreement with the New York stock exchange; we do not study the impact of this merger over herding in the NYSE as the post-merger window in this case would have been far too narrow.

3. Foreign investors are more likely to be informed when trading in a given market in order to counter the perceived informational gap between them and their local counterparts; consequently, a rise in their numbers is expected to be associated with an increase in information-based trading.

4. As Goodhart et al. (1999) have argued, "…regulation should encourage diversification in behavior, and it should check the tendency to herding, since herding worsens systemic risk" (1998, p. 59).

5. This leads to economies of scale, since the platform's fixed costs are defrayed over the trading volume of the whole group (Aggarwal and Dahiya, 2006).

6. Perhaps the simplest case of "correlated signals" for domestic and foreign investors capable of promoting herding in a market relates to macroeconomic information (which involves less ambiguity and effort in terms of collection/observation compared to corporate news) in line with the evidence produced by Chang et al (2000). In a relevant work, Economou et al (2011) provide empirical evidence in favor of the existence of cross-country herding effects between southern European markets.

7. These conditions involve the parallel coexistence of two cascades, one of non-participation (comprised of all investors who delay trading on their signals owing to the presence of transaction costs) and one of limited participation (comprised of those investors riding on the limited information that moves the cascade).

8. One might argue that a highly informative environment would render observational learning less important; with the platform providing the fund manager with a wealth of information, his incentive to observe his peers is expected to decline. However, the gap between "good" and "bad" managers is often not due to information, but rather due to the latter's processing. In other words, even if joining a platform endows a "bad" manager with more information, it is doubtful whether they will grow less dependent on observing their "good" peers if their processing skills are weak.

9. The London International Financial Futures and Options Exchange is a London-based derivatives exchange.

10. The two main EURONEXT-indices are the EURONEXT100 and the NEXT150; the former includes the group's large-caps, while the latter constitutes a mid-cap index.

11. Anonymity was introduced in April 2001; prior to that, broker identifiers appeared on the system's screens.

12. The absence of consistent data-availability prior to 2003 prevented us from presenting data before that year.

13. With the exception of year 2008, as it coincides with the outbreak of the credit crisis.

14. In the case of Portugal foreign investors appear to maintain a relatively stable portion of the market's capitalization throughout the years.

15. Excess returns are calculated by subtracting the risk-free rate for each market from the daily returns (calculated as the difference in the log of daily prices). The proxies for risk-free rates are the 3-month Treasury bill rates for each market adjusted for the daily frequency.

16. We calculated the Fama and French (1993) and Carhart (1997) factors for each market drawing upon the universe of its stocks (active and delisted) during the 1/1/1993 – 31/10/2009 period.

17. The indices used are the Brussels All Shares (Belgium), the SBF250 (France), the AEX (the Netherlands) and the PSI General (Portugal).

18. The 3-month Treasury bill rates used previously to calculate excess returns for each market are used here.

19. We mentioned in the beginning of this section that nine tests are undertaken for each market in each of the two periods (pre-/post-merger). The exceptions in terms of equal-weighted tests for the documented herding significance in the Netherlands pre-merger and Belgium and France post-merger are the two tests that include volatility in their specification. In addition, for the Netherlands and France, the value-weighted test is also an exception.

20. The value of the persistence parameter for the tests including all variables jointly is almost 0.95, while it reaches almost 0.94 in the value-weighted test.

21. The value of the signal-to-noise ratio equals 0.104 for the test controlling for all variables jointly and almost 0.08 for the value-weighted test. Controlling for volatility returns provided us with a signal-to-noise ratio equal to 0.36 which is still higher than its pre-merger values.

22. The fact that the proportion of overseas shareholder-ownership in Portugal stayed relatively constant throughout the years (it hovered within a 40-46% band as table 2 indicates) compared to the other three EURONEXT-markets (where it exhibited increasing trends post-1999) constitutes a possible explanation of why herding remained insignificant in Portugal post-merger. The figures in table 2 suggest that the entry of Portugal in the EURONEXT did not produce a rise in overseas traders' participation as opposed to the rest of the group's markets, thus leaving investors' composition relatively unchanged – and having no effect over herding there.

23. The possibility of herding here being stronger for small stocks is supported by the literature (e.g. Wermers, 1999) according to which investors herd more when trading small caps due to the higher informational and liquidity risks associated with them. The issue here is that small caps tend to enjoy relatively low analyst coverage compared to their larger peers, meaning greater informational uncertainty. As this also implies decreased visibility in the market, these stocks are likely to be less actively traded. Consequently, an investor buying into such a stock might have difficulty selling it at a time of their choice.

24. Results are not reported for reasons of brevity but are available upon request from the authors.

25. With the Netherlands being the sole market producing evidence of herding significance pre-merger and with this significance disappearing once controlling for volatility and for all variables jointly (see table 6; panel A), we tested for herding controlling for all variables excluding volatility; results indicated the significance of herding pre-merger for the Netherlands, thus again confirming the presence of a volatility-effect in our findings.

26. For each test-specification, we obtain h_{mt} from each of its tests (pre-/post-merger), plot herding for each test and then combine the two graphs (pre-/post-merger) into one. For robustness reasons, we also test for each specification on the premise of the full sample period; the final graph for each specification is the same no matter which approach we follow.

27. These graphs are not reported for reasons of space but are available upon request from the authors.

28. In view of the global credit crisis and its impact on international markets, we repeated all our post-merger tests using August 2008 as the end-date to exclude any possible effect of this crisis. Our tests produced evidence similar to that of the original post-merger period tests. Results are available from the authors upon request.

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Table 1: Trading activity in EURONEXT's European equity markets

	Belgium	France	Netherlands	Portugal
Panel A: Equity turnover				
2003	33,755	877,798	429,022	19,020
2004	55,867	993,926	465,831	27,343
2005	91,049	1,103,352	558,693	30,352
2006	103,374	1,534,832	686,956	50,313
2007	158,887	1,991,768	1,057,399	94,531
2008	137,219	1,733,810	697,718	54,791
Panel B: Market capitalization				
2003	137,593	1,074,978	387,400	46,208
2004	201,028	1,147,037	396,295	51,676
2005	244,574	1,490,868	502,606	56,780
2006	300,454	1,841,586	591,205	79,016
2007	263,718	1,874,393	654,012	90,451
2008	120,013	1,056,746	278,985	49,432

The figures reported above are expressed in € million. Source: Euronext

Table 2: Evolution of investors' composition in EURONEXT's European markets

	Domestic institutional investors[a]				Domestic individual investors				Overseas investors				Others[b]			
	BE	FR	NL	PT	BE	FR	NL	PT	BE	FR	NL	PT	BE	FR	NL	PT
1993	17.5	NA	NA	NA	23.6	NA	NA	NA	21.1	NA	NA	NA	37.8	NA	NA	NA
1994	20.1	NA	NA	NA	20.5	NA	NA	NA	21.8	NA	NA	NA	37.7	NA	NA	NA
1995	21.6	26.3	NA	NA	18.3	13.4	NA	NA	22.9	24.9	NA	NA	37.2	35.4	NA	NA
1996	22.4	27.6	NA	NA	15.9	12.4	NA	NA	22.7	28.0	NA	NA	39.1	31.9	NA	NA
1997	22.4	28.3	NA	NA	13.5	9.9	NA	NA	26.9	31.1	NA	NA	37.2	30.7	NA	NA
1998	23.3	27.9	NA	NA	17.9	9.1	NA	NA	23.0	31.9	NA	NA	35.7	31.1	NA	NA
1999	24.7	27.5	NA	NA	14.2	7.2	NA	NA	30.4	38.1	NA	NA	30.7	27.2	NA	NA
2000	20.3	28.8	NA	13.0	15.4	7.4	NA	15.0	31.1	38.8	NA	42.1	33.2	24.9	NA	29.9
2001	21.8	30.4	NA	15.0	11.5	6.8	NA	14.3	35.7	38.9	NA	44.9	31.1	23.8	NA	25.8
2002	26.9	30.6	12.0	17.8	10.2	6.7	9.0	12.1	28.3	38.5	67.0	45.9	34.5	24.2	12.0	24.3
2003	25.0	29.4	12.0	18.5	14.5	6.7	11.0	12.4	30.4	37.5	69.0	41.8	30.2	26.5	8.0	27.4
2004	22.7	31.4	NA	20.5	19.7	7.7	NA	12.7	28.8	40.0	NA	40.0	28.8	20.4	NA	26.9
2005	19.0	28.5	NA	20.6	20.3	7.1	NA	12.6	36.2	40.5	80.0[c]	39.8	24.4	23.6	NA	27.0
2006	18.0	29.0	8.1	20.7	19.8	5.8	4.5	11.1	37.8	40.7	79.0	42.8	24.5	24.5	8.4	25.4
2007	18.7	28.8	8.9	19.9	19.5	6.7	3.6	9.9	38.7	41.1	71.0	44.8	23.1	23.4	16.5	25.3

The above table presents the percentage participation of each investor-type in the market capitalization of Belgium (BE), France (FR), the Netherlands (NL) and Portugal (PT). Data were obtained from the 2008 shareownership survey conducted on behalf of the Federation of European Securities Exchanges (FESE).

[a] "Domestic institutional investors" include the following sub-categories: pension funds; insurance companies; mutual funds; and collective financial investment companies.

[b] "Others" include the following sub-categories: commercial/savings banks; mortgage banks; limited companies; private organizations and trusts; and the public sector.

[c] The decomposition of investor-participation for year 2005 in the Netherlands was conducted using the dual distinction between domestic versus overseas investors, hence it is not possible to distinguish percentages for the categories "domestic institutional investors", "domestic individual investors" and "others".

Table 3: Properties of the logarithmic cross-sectional standard deviations of betas on the market returns

	Belgium		France		Netherlands		Portugal	
Panel A: Equal-weighted logarithmic cross-sectional standard deviation of Carhart-betas on the market returns								
	Pre-merger (January 1993 – September 2000)	Post-merger (October 2000 – October 2009)	Pre-merger (January 1993 – September 2000)	Post-merger (October 2000 – October 2009)	Pre-merger (January 1993 – September 2000)	Post-merger (October 2000 – October 2009)	Pre-merger (January 1993 – March 2002)	Post-merger (April 2002 – October 2009)
Mean	-0.1086	-0.1492	0.1954	0.0021	-0.0589	-0.0094	-0.1086	-0.1244
Standard deviation	0.0876	0.1598	0.1256	0.1287	0.0835	0.0058	0.0776	0.0988
Skewness	-0.0776	-0.1492	0.2293	0.1841	-0.0493	-0.0058	-0.0776	-0.0931
Kurtosis	-0.1975	-0.2822	0.5575	0.6542	0.6171	0.7592	-0.1975	-0.2455
Jarque-Bera	0.5312	0.5101	4.3875	3.9423	3.2935	2.8425	0.5312	0.6492
Panel B: Value-weighted logarithmic cross-sectional standard deviation of Carhart-betas on the market returns								
Mean	-0.5547	-0.4384	0.0412	0.0735	-0.6308	-0.7803	-0.3720	-0.3661
Standard deviation	0.2988	0.4283	0.1992	0.2127	0.5538	0.5461	0.3801	0.2548
Skewness	0.4186	0.2175	0.2957	0.2901	0.2965	0.3472	0.4083	0.4593
Kurtosis	0.4614	0.3294	-0.3295	-0.3375	-0.2796	-0.2065	-0.5697	-0.6088
Jarque-Bera	4.9518	4.9270	0.7067	1.1021	2.6691	1.4354	5.7438	4.2581

The logarithmic cross-sectional dispersion of betas is calculated here using betas of market returns estimated with ordinary least squares from the Carhart (1997) model. For each month, we used daily data to obtain OLS estimates of the betas and then these betas were used to obtain the cross-sectional beta-dispersion. (*) Indicates significance at the 5 percent level.

Table 4: Herding Results for Belgium

	Original herding model	Herding model controlling for market direction	Herding model controlling for volatility	Herding model controlling for SMB-factor	Herding model controlling for HML-factor	Herding model controlling for WML-factor	Herding model controlling for Treasury-bill rate	Herding model controlling for All factors	Value-weighted herding model
Panel A: Pre-merger									
φ_m	0.8848 (0.0601)*	0.8872 (0.0598)*	0.9195 (0.0511)*	0.8843 (0.0602)*	0.8877 (0.0593)*	0.8833 (0.0612)*	0.8934 (0.0570)*	0.9187 (0.0517)*	0.7746 (0.1435)*
μ_m	-0.0783 (0.0186)*	-0.0794 (0.0183)*	-0.0665 (0.0167)*	-0.0782 (0.0186)*	-0.0787 (0.0187)*	-0.0804 (0.0182)*	-0.1082 (0.0191)*	-0.0683 (0.0165)*	-0.5128 (0.0390)*
c_1		0.0364 (0.0856)						-0.1881 (0.0471)*	
c_2			-0.1796 (0.0476)*					-0.0470 (0.0800)	
c_3				0.0552 (0.2396)				0.1942 (0.2271)	
c_4					0.0703 (0.2169)			0.1028 (0.2030)	
c_5						0.1571 (0.2194)		0.2945 (0.2050)	
c_6							0.0059 (0.0034)	-0.00003 (0.0029)	
$\sigma^2_{m,\eta}$	0.0005 (0.0003)	0.0004 (0.0002)	0.0002 (0.0001)	0.0005 (0.0003)	0.0005 (0.0003)	0.0005 (0.0003)	0.0004 (0.0002)	0.0002 (0.0001)	0.0041 (0.0035)
$\sigma^2_{m,\upsilon}$	0.0045 (0.0008)*	0.0046 (0.0002)*	0.0043 (0.0007)*	0.0045 (0.0008)*	0.0046 (0.0008)*	0.0046 (0.0008)*	0.0045 (0.0008)*	0.0043 (0.0007)*	0.0668 (0.0108)*
$\sigma_{m,\eta}/_{S.D.} \log [\, Std_c(\beta^b_{imt}) \,]$	0.2476	0.2384	0.1620	0.2498	0.2441	0.2441	0.2396	0.1608	0.2217

Panel B: Post-merger

φ_m	0.6045	0.5599	0.9510	0.6299	0.6264	0.6354	0.6187	0.9423	0.6498
	(0.1013)*	(0.1112)*	(0.0957)*	(0.0981)*	(0.0986)*	(0.0987)*	(0.0984)*	(0.0313)*	(0.0952)*
μ_m	-0.1301	-0.1303	-0.0788	-0.1304	-0.1322	-0.1290	-0.1410	-0.0747	-0.6900
	(0.0138)*	(0.0124)*	(0.0063)*	(0.0143)*	(0.0141)*	(0.0141)*	(0.0140)*	(0.0131)*	(0.0451)*
c_1		0.1246						-0.2241	
		(0.0719)						(0.0256)*	
c_2			-0.2275					-0.0254	
			(0.0180)*					(0.0490)	
c_3				0.0718				0.1840	
				(0.1445)				(0.1128)	
c_4					0.1156			0.0707	
					(0.1139)			(0.0848)	
c_5						-0.0177		-0.0279	
						(0.0446)		(0.0392)	
c_6							0.0039	0.0029	
							(0.0045)	(0.0039)	
$\sigma^2_{m,\eta}$	0.0030	0.0028	0.000004	0.0028	0.0028	0.0026	0.0029	0.0001	0.0247
	(0.0007)*	(0.0007)*	(0.00001)	(0.0007)*	(0.0007)*	(0.0007)*	(0.0007)*	(0.0001)	(0.0067)*
$\sigma^2_{m,\upsilon}$	0.0027	0.0028	0.0040	0.0028	0.0028	0.0030	0.0028	0.0038	0.0294
	(0.0007)*	(0.0007)*	(0.0005)*	(0.0007)*	(0.0007)*	(0.0007)*	(0.0007)*	(0.0004)*	(0.0068)*
$\sigma_{m,\eta}/\text{S.D.} \log[Std_c(\beta^b_{imt})]$	0.6207	0.5990	0.0216	0.6001	0.6035	0.5784	0.6035	0.1209	0.54636

The sample window for the above estimations ranges between: January 1993 – September 2000 (panel A) and October 2000 - October 2009 (panel B). With the cross-sectional beta-dispersion calculated each month using daily data, we end up with 202 monthly observations (93 pre-merger; 109 post-merger) which constitute our input here in the logarithmic form. The calculations are performed here on the basis of all (active; dead; suspended) stocks of the Belgian market. The above table contains the estimates from the tests of the Hwang and Salmon (2004) model using the nine specifications outlined in section 4: equal-weighted beta dispersion; value-weighted beta-dispersion; equal-weighted beta-dispersion with volatility as control variable; equal-weighted beta-dispersion with market index as control variable; equal-weighted beta dispersion with SMB as control variable; equal-weighted beta dispersion with HML as control variable; equal-weighted beta dispersion with WML as control variable; equal-weighted beta dispersion with 3-month treasury bill rate as control variable; equal-weighted beta dispersion with all these control variables included jointly. S. D. $\log[Std_c(\beta^b_{imt})]$ here represents the time series standard deviation of the logarithmic cross-sectional standard deviation of the estimated betas. Brackets include standard errors of our estimates and “*” indicates significance at the 5 percent level

Table 5: Herding Results for France

	Original herding model	Herding model controlling for market direction	Herding model controlling for volatility	Herding model controlling for SMB-factor	Herding model controlling for HML-factor	Herding model controlling for WML-factor	Herding model controlling for Treasury-bill rate	Herding model controlling for All factors	Value-weighted herding model
Panel A: Pre-merger									
φ_m	0.8558	0.8666	0.8193	0.8562	0.8655	0.8549	0.8501	0.7521	0.9149
	(0.0742)*	(0.0715)*	(0.1937)*	(0.0732)*	(0.0716)*	(0.0747)*	(0.0770)*	(0.2901)*	(0.0547)*
μ_m	0.1695	0.1679	0.2389	0.1700	0.1714	0.1695	0.1440	0.2520	0.0411
	(0.0208)*	(0.0208)*	(0.0116)*	(0.0212)*	(0.0210)*	(0.0208)*	(0.0202)*	(0.0109)*	(0.1134)
c_1		0.0771						-0.3260	
		(0.0988)						(0.0374)*	
c_2			-0.3084					0.0946	
			(0.0393)*					(0.0914)	
c_3				0.3635				0.7622	
				(0.4632)				(0.4303)	
c_4					-0.1149			-0.0285	
					(0.2386)			(0.2163)	
c_5						-0.0131		-0.0999	
						(0.2288)		(0.2138)	
c_6							0.0047	-0.0024	
							(0.0034)	(0.0021)	
$\sigma^2_{m,\eta}$	0.0008	0.0007	0.0001	0.0008	0.0007	0.0008	0.0008	0.0002	0.0100
	(0.0004)	(0.0004)	(0.0002)	(0.0005)	(0.0004)	(0.0005)	(0.0004)	(0.0003)	(0.0065)
$\sigma^2_{m,\upsilon}$	0.0082	0.0083	0.0084	0.0081	0.0083	0.0082	0.0082	0.0081	0.2134
	(0.0014)*	(0.0014)*	(0.0013)*	(0.0014)*	(0.0014)*	(0.0014)*	(0.0014)*	(0.0012)*	(0.0341)*
$\sigma_{m,\eta}/\text{S.D.} \log [\, Std_c(\beta^b_{imt}) \,]$	0.2236	0.2077	0.0947	0.2292	0.2125	0.2244	0.2228	0.1106	0.1826

Panel B: Post-merger

φ_m	0.5735 (0.1360)*	0.5848 (0.1267)*	0.6110 (0.1759)*	0.5626 (0.1336)*	0.5619 (0.1330)*	0.5630 (0.1309)*	0.5618 (0.1350)*	0.9495 (0.1990)*	0.9397 (0.0495)*
μ_m	0.2240 (0.0182)*	0.2232 (0.0188)*	0.3109 (0.0152)*	0.2232 (0.0183)*	0.2235 (0.0183)*	0.2227 (0.0184)*	0.2372 (0.0180)*	0.3536 (0.0929)*	-0.4566 (0.0588)*
c_1		-0.0996 (0.1094)						-0.3492 (0.0841)*	
c_2			-0.2535 (0.0361)*					-0.0847 (0.1187)	
c_3				0.0060 (0.0101)				0.1362 (0.1949)	
c_4					-0.0040 (0.0068)			0.2980 (0.1415)*	
c_5						0.0098 (0.0102)		0.3173 (0.0846)*	
c_6							-0.0046 (0.0058)	-0.0056 (0.0127)	
$\sigma^2_{m,\eta}$	0.0047 (0.0017)*	0.0049 (0.0017)*	0.0020 (0.0012)	0.0051 (0.0018)*	0.0051 (0.0018)*	0.0052 (0.0018)*	0.0048 (0.0018)*	0.0002 (0.0005)	0.0019 (0.0012)
$\sigma^2_{m,\upsilon}$	0.0110 (0.0021)*	0.0106 (0.0021)*	0.0120 (0.0019)*	0.0106 (0.0021)*	0.0106 (0.0021)*	0.0104 (0.0021)*	0.0109 (0.0021)*	0.0115 (0.0018)*	0.0373 (0.0059)*
$\sigma_{m,\eta}/_{S.D.}\log[Std_c(\beta^b_{imt})]$	0.5436	0.5588	0.3590	0.5651	0.5667	0.5683	0.5540	0.1042	0.0795

The sample window for the above estimations ranges between: January 1993 – September 2000 (panel A) and October 2000 - October 2009 (panel B). With the cross-sectional beta-dispersion calculated each month using daily data, we end up with 202 monthly observations (93 pre-merger; 109 post-merger) which constitute our input here in the logarithmic form. The calculations are performed here on the basis of all (active; dead; suspended) stocks of the French market. The above table contains the estimates from the tests of the Hwang and Salmon (2004) model using the nine specifications outlined in section 4: equal-weighted beta dispersion; value-weighted beta-dispersion; equal-weighted beta-dispersion with volatility as control variable; equal-weighted beta-dispersion with market index as control variable; equal-weighted beta dispersion with SMB as control variable; equal-weighted beta dispersion with HML as control variable; equal-weighted beta dispersion with WML as control variable; equal-weighted beta dispersion with 3-month treasury bill rate as control variable; equal-weighted beta dispersion with all these control variables included jointly. S. D. $\log[Std_c(\beta^b_{imt})]$ here represents the time series standard deviation of the logarithmic cross-sectional standard deviation of the estimated betas. Brackets include standard errors of our estimates and "*" indicates significance at the 5 percent level

Table 6: Herding Results for the Netherlands

	Original herding model	Herding model controlling for market direction	Herding model controlling for volatility	Herding model controlling for SMB-factor	Herding model controlling for HML-factor	Herding model controlling for WML-factor	Herding model controlling for Treasury-bill rate	Herding model controlling for All factors	Value-weighted herding model
Panel A: Pre-merger									
φ_m	0.9705 (0.0266)*	0.9711 (0.0264)*	0.9174 (0.0583)*	0.9707 (0.0265)*	0.9717 (0.0263)*	0.9707 (0.0265)*	0.9699 (0.0269)*	0.9528 (0.0436)*	-0.5667 (0.5343)
μ_m	0.0082 (0.0311)	0.0063 (0.0309)	0.0010 (0.0164)	0.0092 (0.0315)	0.0112 (0.0321)	0.0081 (0.0311)	0.0224 (0.0310)	-0.4370 (0.0225)*	-0.3211 (0.0425)*
c_1		0.0380 (0.0750)						-0.2556 (0.0442)*	
c_2			-0.2144 (0.0415)*					-0.1805 (0.0659)*	
c_3				0.1132 (0.2915)				-0.1422 (0.2572)	
c_4					-0.3353 (0.1717)			-0.3486 (0.1531)*	
c_5						0.0258 (0.0745)		0.0415 (0.0655)	
c_6							-0.0001 (0.0003)	0.0040 (0.0002)*	
$\sigma^2_{m,\eta}$	0.0003 (0.0002)*	0.0003 (0.0002)*	0.0002 (0.0001)	0.0004 (0.0002)*	0.0004 (0.0002)*	0.0003 (0.0002)*	0.0003 (0.0002)*	0.0002 (0.0001)	0.0053 (0.0127)
$\sigma^2_{m,\upsilon}$	0.0039 (0.0006)*	0.0039 (0.0006)*	0.0035 (0.0006)*	0.0039 (0.0006)*	0.0037 (0.0006)*	0.0039 (0.0006)*	0.0039 (0.0006)*	0.0031 (0.0005)*	0.1461 (0.0240)*
$\sigma_{m,\eta}/_{\text{S.D.}} \log [\, Std_c(\beta^b_{imt}) \,]$	0.3686	0.2166	0.1747	0.2238	0.2310	0.2190	0.2202	0.1819	0.1358

Panel B: Post-merger

φ_m	0.6718	0.6885	0.8647	0.6658	0.6738	0.6720	0.6659	0.8392	0.9995
	(0.0784)*	(0.0791)*	(0.0531)*	(0.0814)*	(0.0784)*	(0.0787)*	(0.0790)*	(0.0582)*	(0.0134)*
μ_m	-0.0639	-0.0624	0.0235	-0.0627	-0.0641	-0.0605	0.1848	0.1288	-0.4044
	(0.0168)*	(0.0160)*	(0.0202)	(0.0157)*	(0.0169)*	(0.0165)*	(0.0165)*	(0.0182)*	(0.1819)*
c_1		0.1330						-0.2554	
		(0.0500)*						(0.0299)*	
c_2			-0.2411					-0.0538	
			(0.0315)*					(0.0430)	
c_3				-0.3347				-0.0922	
				(0.1933)				(0.1625)	
c_4					0.0120			0.0848	
					(0.1271)			(0.1055)	
c_5						-0.1660		-0.2135	
						(0.0865)		(0.0739)*	
c_6							-0.0021	-0.0010	
							(0.0001)*	(0.0002)*	
$\sigma^2_{m,\eta}$	0.0034	0.0028	0.0010	0.0030	0.0034	0.0033	0.0034	0.0011	0.0069
	(0.0006)*	(0.0006)*	(0.0003)*	(0.0006)*	(0.0006)*	(0.0006)*	(0.0006)*	(0.0003)*	(0.0035)*
$\sigma^2_{m,\upsilon}$	0.0010	0.0013	0.0019	0.0012	0.0010	0.0010	0.0010	0.0016	0.1268
	(0.0004)*	(0.0004)*	(0.0004)*	(0.0006)*	(0.0004)*	(0.0004)*	(0.0004)*	(0.0003)*	(0.0187)*
$\sigma_{m,\eta}/_{S.D.}\log[Std_c(\beta^b_{imt})]$	0.7002	0.6284	0.3794	0.6571	0.6990	0.6858	0.7002	0.3938	0.1542

The sample window for the above estimations ranges between: January 1993 – September 2000 (panel A) and October 2000 - October 2009 (panel B). With the cross-sectional beta-dispersion calculated each month using daily data, we end up with 202 monthly observations (93 pre-merger; 109 post-merger) which constitute our input here in the logarithmic form. The calculations are performed here on the basis of all (active; dead; suspended) stocks of the Dutch market. The above table contains the estimates from the tests of the Hwang and Salmon (2004) model using the nine specifications outlined in section 4: equal-weighted beta dispersion; value-weighted beta-dispersion; equal-weighted beta-dispersion with volatility as control variable; equal-weighted beta-dispersion with market index as control variable; equal-weighted beta dispersion with SMB as control variable; equal-weighted beta dispersion with HML as control variable; equal-weighted beta dispersion with WML as control variable; equal-weighted beta dispersion with 3-month treasury bill rate as control variable; equal-weighted beta dispersion with all these control variables included jointly. S. D. $\log[Std_c(\beta^b_{imt})]$ here represents the time series standard deviation of the logarithmic cross-sectional standard deviation of the estimated betas. Brackets include standard errors of our estimates and "*" indicates significance at the 5 percent level

Table 7: Herding Results for Portugal

	Original herding model	Herding model controlling for market direction	Herding model controlling for volatility	Herding model controlling for SMB-factor	Herding model controlling for HML-factor	Herding model controlling for WML-factor	Herding model controlling for Treasury-bill rate	Herding model controlling for All factors	Value-weighted herding model
Panel A: Pre-merger									
φ_m	0.9058 (0.0628)*	0.8989 (0.0619)*	0.8838 (0.2023)*	0.8978 (0.0650)*	0.9093 (0.0583)*	0.9060 (0.0621)*	0.9057 (0.0550)*	0.8994 (0.0897)*	0.9963 (0.0191)*
μ_m	0.1883 (0.0246)*	0.1811 (0.0250)*	0.2279 (0.0133)*	0.1896 (0.0243)*	0.1835 (0.0263)*	0.1863 (0.0245)*	-0.6396 (0.0268)*	0.3326 (0.0153)*	0.0823 (0.1517)
c_1		0.2571 (0.1143)*						-0.3408 (0.0466)*	
c_2			-0.2775 (0.0447)*					0.1813 (0.0958)	
c_3				0.2361 (0.1364)				0.2685 (0.1150)*	
c_4					0.1097 (0.0883)			0.2288 (0.0738)*	
c_5						0.0018 (0.0014)		0.0012 (0.0012)	
c_6							0.0079 (0.0003)*	-0.0011 (0.0001)*	
$\sigma^2_{m,\eta}$	0.0005 (0.0004)	0.0007 (0.0004)	0.0001 (0.0002)	0.0006 (0.0004)	0.0006 (0.0004)	0.0005 (0.0004)	0.0007 (0.0004)	0.0002 (0.0002)	0.0053 (0.0038)
$\sigma^2_{m,\upsilon}$	0.0181 (0.0026)*	0.0170 (0.0025)*	0.0159 (0.0022)*	0.0175 (0.0025)*	0.0176 (0.0025)*	0.0178 (0.0026)*	0.0173 (0.0025)*	0.0131 (0.0018)*	0.0798 (0.0140)*
$\sigma_{m,\eta}$/S.D. log [$Std_c(\beta^b_{imt})$]	0.1508	0.1664	0.0487	0.1612	0.1612	0.1501	0.1716	0.0253	0.2040

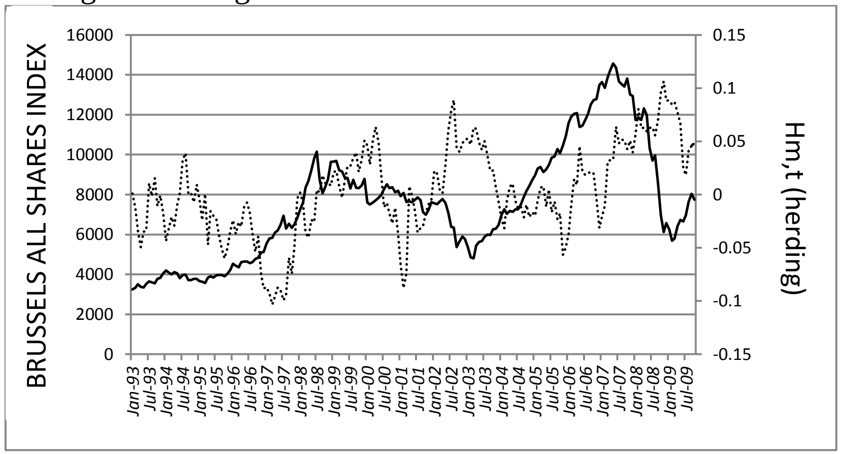
Panel B: Post-merger

φ_m	0.9215 (0.0469)*	0.9274 (0.0459)*	0.2464 (0.1828)	0.9222 (0.0466)*	0.9259 (0.0458)*	0.9214 (0.0469)*	0.9278 (0.0450)*	0.4781 (0.3821)	0.7915 (0.0951)*
μ_m	0.1457 (0.0441)*	0.1455 (0.0421)*	0.2174 (0.0160)*	0.1459 (0.0444)*	0.1397 (0.0428)*	0.1456 (0.0440)*	0.9508 (0.0446)*	0.9143 (0.0133)*	-0.4799 (0.0521)*
c_1		0.1785 (0.1388)						-0.3700 (0.0456)*	
c_2			-0.3742 (0.0546)*					-0.0336 (0.1160)	
c_3				-0.0246 (0.1032)				-0.0369 (0.0882)	
c_4					0.1018 (0.0691)			0.1664 (0.0576)*	
c_5						0.0045 (0.0476)		-0.0786 (0.0437)	
c_6							-0.0082 (0.0005)*	-0.0071 (0.0001)*	
$\sigma^2_{m,\eta}$	0.0016 (0.0008)	0.0012 (0.0007)	0.0086 (0.0025)*	0.0016 (0.0008)	0.0013 (0.0007)	0.0016 (0.0008)	0.0014 (0.0008)	0.0013 (0.0015)	0.0091 (0.0048)
$\sigma^2_{m,\upsilon}$	0.0167 (0.0028)*	0.0170 (0.0028)*	0.0083 (0.0025)*	0.0167 (0.0028)*	0.0167 (0.0028)*	0.0167 (0.0028)*	0.0168 (0.0028)*	0.0156 (0.0023)*	0.0584 (0.0104)*
$\sigma_{m,\eta}$/S.D. log [$Std_c(\beta^b_{imt})$]	0.0104	0.2288	0.6032	0.0812	0.2372	0.2567	0.2450	0.2353	0.2671

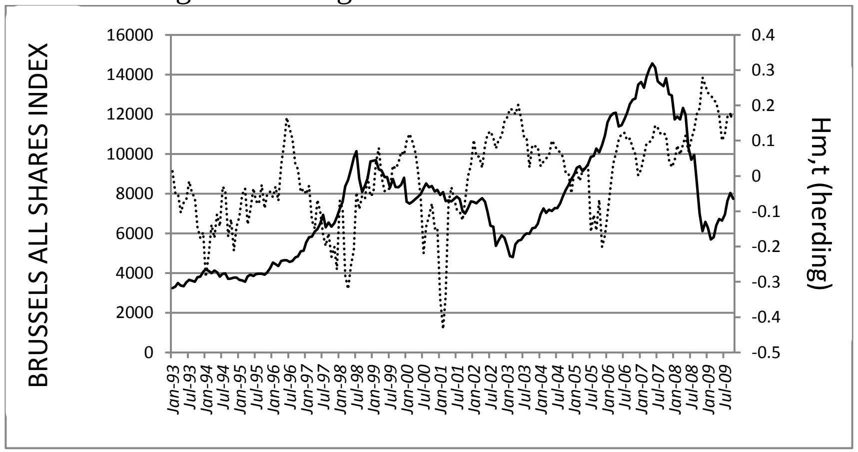
The sample window for the above estimations ranges between: January 1993 – March 2002 (panel A) and April 2002 - October 2009 (panel B). With the cross-sectional beta-dispersion calculated each month using daily data, we end up with 202 monthly observations (111 pre-merger; 91 post-merger) which constitute our input here in the logarithmic form. The calculations are performed here on the basis of all (active; dead; suspended) stocks of the Portuguese market. The above table contains the estimates from the tests of the Hwang and Salmon (2004) model using the nine specifications outlined in section 4: equal-weighted beta dispersion; value-weighted beta-dispersion; equal-weighted beta-dispersion with volatility as control variable; equal-weighted beta-dispersion with market index as control variable; equal-weighted beta dispersion with SMB as control variable; equal-weighted beta dispersion with HML as control variable; equal-weighted beta dispersion with WML as control variable; equal-weighted beta dispersion with 3-month treasury bill rate as control variable; equal-weighted beta dispersion with all these control variables included jointly. S. D. $\log[Std_c(\beta^b_{imt})]$ here represents the time series standard deviation of the logarithmic cross-sectional standard deviation of the estimated betas. Brackets include standard errors of our estimates and "*" indicates significance at the 5 percent level.

Figure 1: Belgium Herding Charts

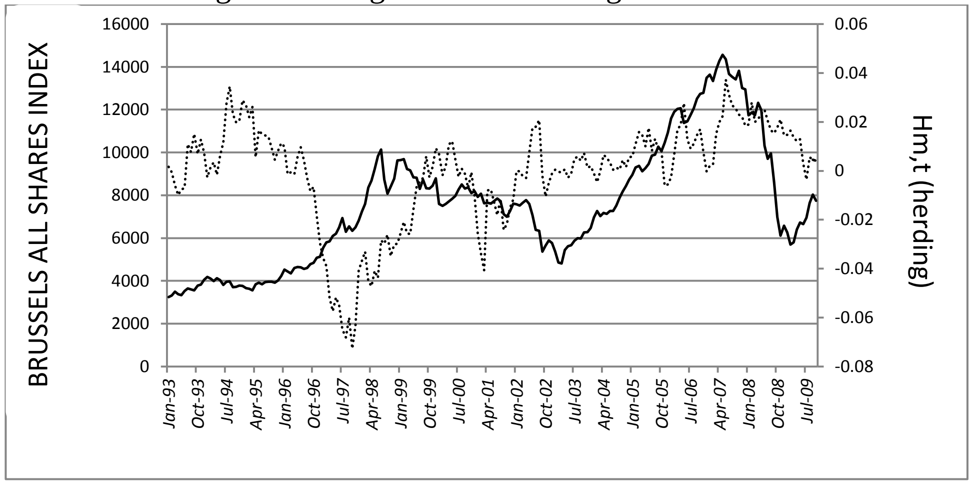
a. Original herding model



b. Value-weighted herding mode



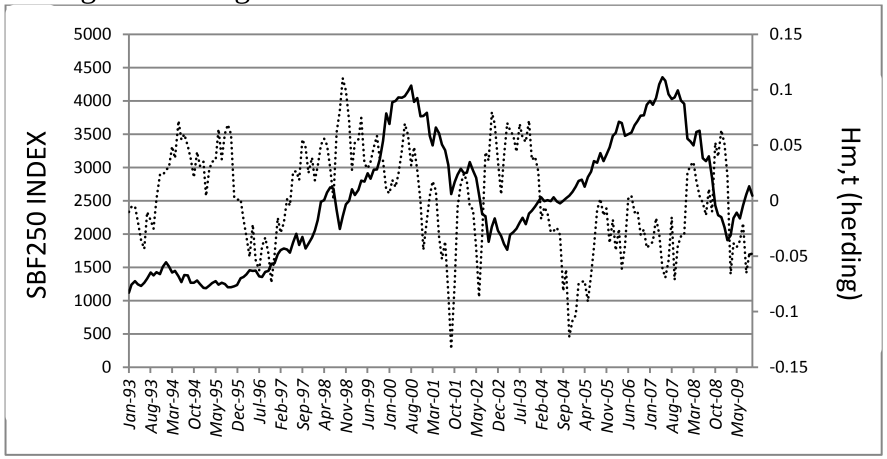
c. Original herding model controlling for all variables



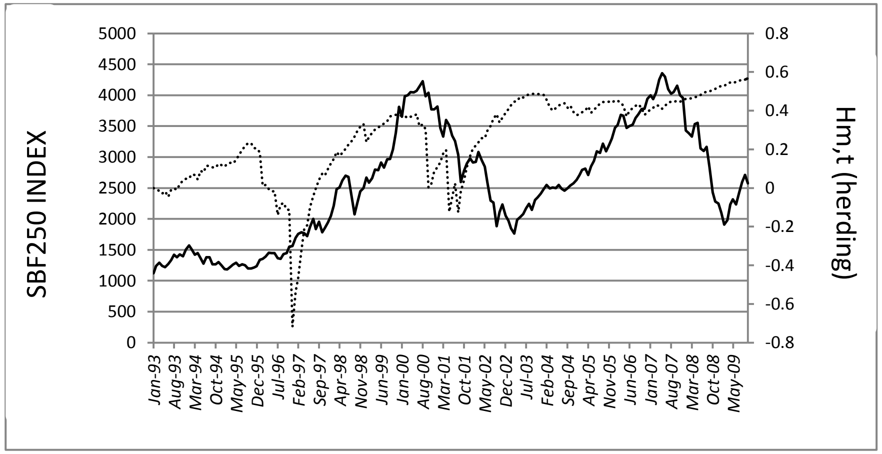
NB. Herding is represented through the dotted line while the continuous line indicates the market index

Figure 2: France Herding Charts

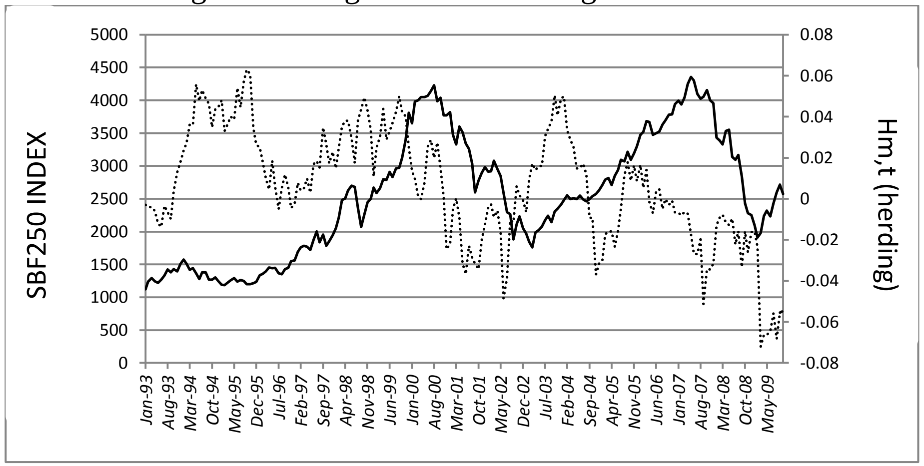
a. Original herding model



b. Value-weighted herding model



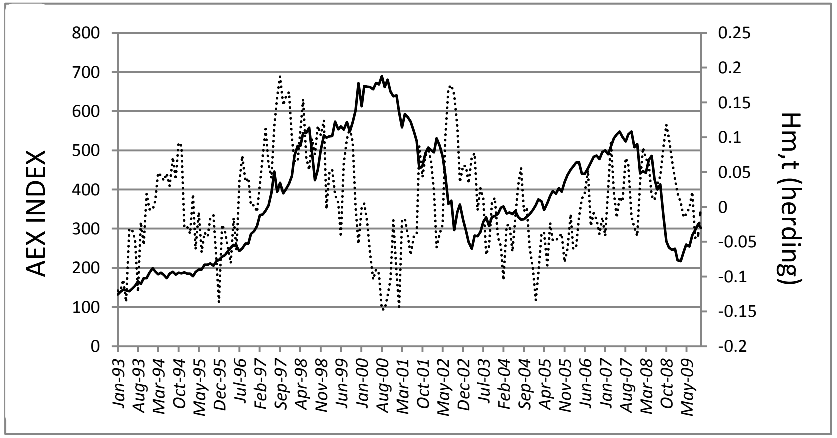
c. Original herding model controlling for all variables



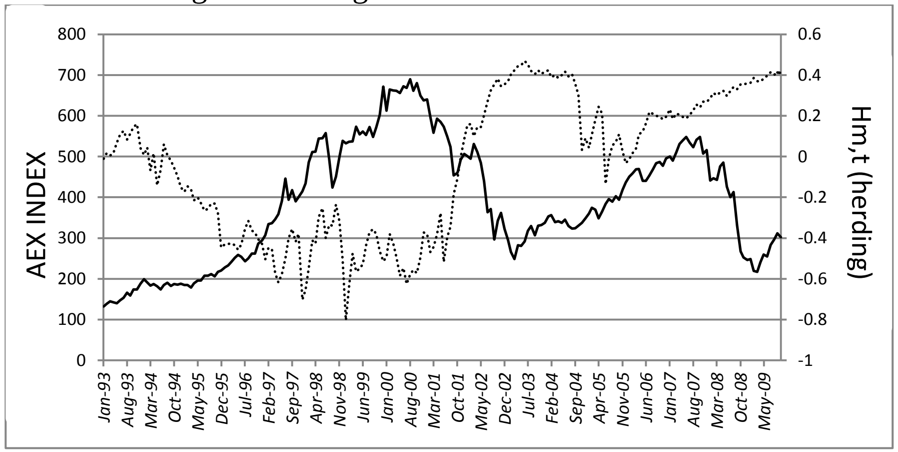
NB. Herding is represented through the dotted line while the continuous line indicates the market index

Figure 3: The Netherlands Herding Charts

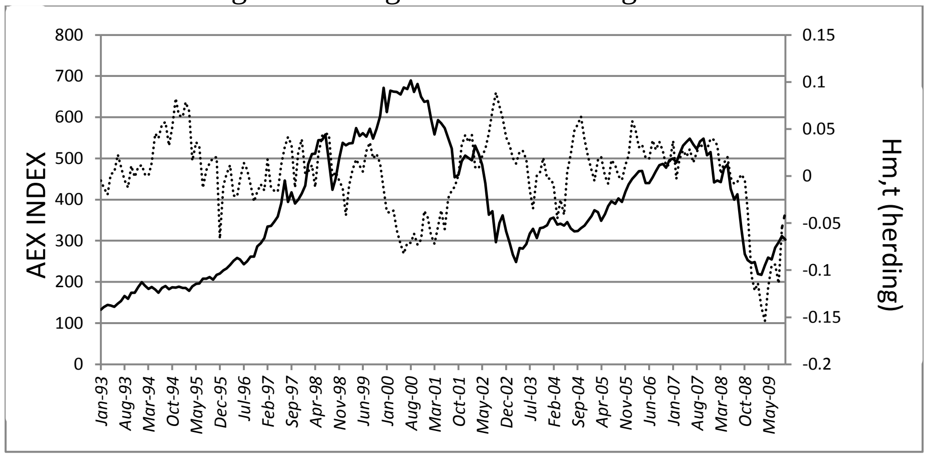
a. Original herding model



b. Value-weighted herding model



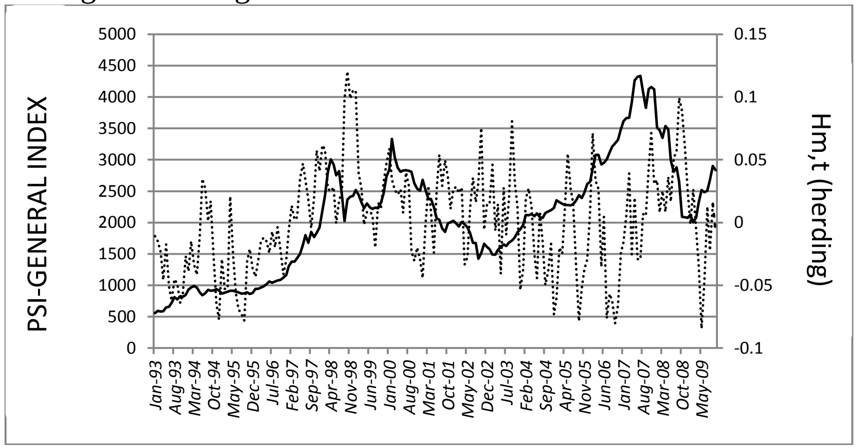
c. Original herding model controlling for all variables



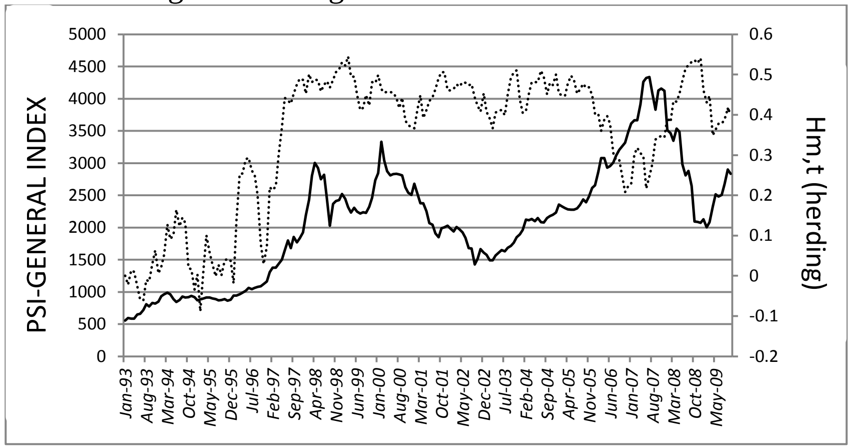
NB. Herding is represented through the dotted line while the continuous line indicates the market index

Figure 4: Portugal Herding Charts

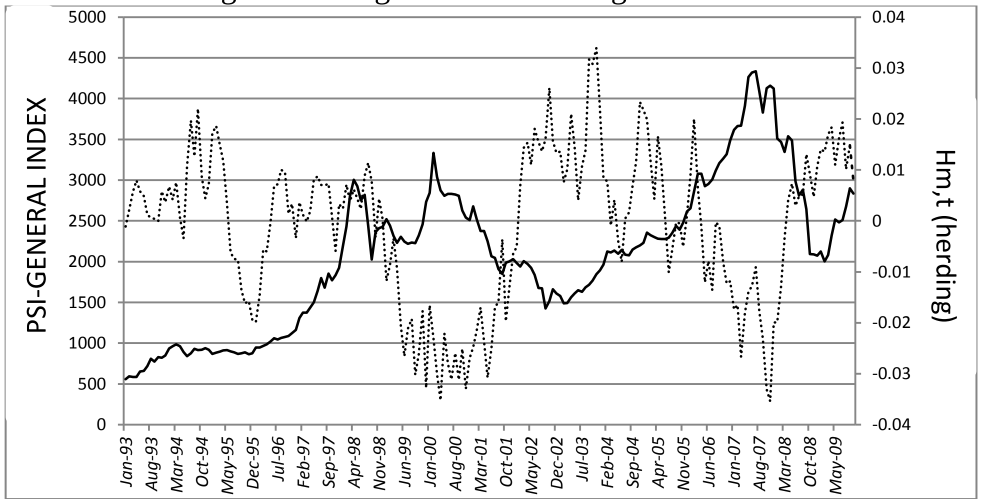
a. Original herding model



b. Value-weighted herding model



c. Original herding model controlling for all variables



NB. Herding is represented through the dotted line while the continuous line indicates the market index